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Actionable Cultural Understanding for Support to Tactical Operations (ACUSTO)

Toward a New Methodological Template for Spatial Decision Support System

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and Martin J. Savoie

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Abstract: This report approaches the development of actionable intelligence for counterinsurgency by drawing parallels with the study of criminal events such as homicides, vehicle thefts, and gang violence, and by exploiting the methodological approaches that emphasize spatially explicit information. This spatial analysis of crime builds on the well-established methods of spatial data analysis and spatial statistics, and applies these in the context of criminal events that happen at specific locations. The theoretical background for these methods is drawn from environmental criminology. Methods are categorized into three main groups: exploratory spatial data analysis, explanatory spatial modeling, and surveillance/forecasting techniques. The basic principles are outlined and examples provided that illustrate the application specific techniques in crime analysis. An initial methodological template is formulated that stresses the constraints imposed by the quality and quantity of spatially specific information available in a counterinsurgency context.

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Preface

This study was conducted for the Assistant Secretary of the Army for Acquisition, Logistics, and Technology (ASAALT) under Project 62784AT41, “Military Facilities Engineering Technology,” Work Unit 21 2040, “Social-Cultural and Environmental Data Fusion Models.”

The work was completed under the direction of the Ecological Process Branch (CN-N) of the Installations Division (CN), Construction Engineering Research Laboratory (CERL). The CERL Project Manager was William D. Meyer. The Field Investigation work was done by Dr. Luc Anselin, of the University of Illinois, under contract W9132T-07-T-0065. Alan B. Anderson is Chief, CN-N, and Dr. John T. Bandy is Chief, CN. The associated Technical Director was Dr. William D. Severinghaus. The Director of CERL is Dr. Ilker Adiguzel.

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1 Introduction

Background

Developing cultural information into cultural knowledge for military operations is predominantly an intelligence activity that takes place within the military decision making process (MDMP). MDMP includes mission analysis, which produces an intelligence assessment, evaluation of courses of action and re-evaluation of intelligence assessment. Intelligence Preparation of the Battlefield (IPB) is performed before, during, and after the mission analysis phase of the MDMP. Recent Army field manuals and lessons learned documents emphasize the role of Every Soldier as Sensor (ES2) in providing information for IPB. The incorporation of cultural knowledge into IPB is recognized as especially critical for planning and implementing counterinsurgency operations.

In practice, IPB involves collecting data manually or through sensors coupled with computer analysis by highly trained intelligence analysts. The products produced from these efforts are routinely classified and subsequently unusable by the tactical war fighter operating at the brigade combat team level. Beyond the brief cultural training that brigade combat teams receive shortly before deployment, there are few, if any, resources to draw on for cultural information while in theater. Cultural “knowledge” is gained through experience in theater. There is little cumulative storage of this information and no formal process to pass this knowledge on to the next replacement unit.

Objective

The goal of the Actionable Cultural Understanding for Support to Tactical Operations (ACUSTO) project is to provide a product for enhanced cultural understanding that will be accessible to the tactical war fighter and programmable into tactical spatial objects for a possible future web-enabled decision support system.

Approach

Dr. Luc Anselin Director of Geographical Sciences at Arizona State University and a National Academy of Sciences Scholar in Geography a collaborator on the ACUSTO project was asked to provide an analysis of methodologies, knowledge systems, and spatial analytical techniques in light on

the need for socio-cultural content that must be considered to achieve a future spatial decision support system to take the MDMP to its next future state and provide the foundation for geographic evidential reasoning models. Provided in the following pages is Dr. Anselin's report documenting this analysis, which concludes with an outline for a methodological template for a future spatial decision support system to support MDMP and Geographic Evidential Reasoning Models.

Mode of technology transfer

It is anticipated that the use of open source data to provide cultural understanding in the operational environment will allow dissemination of cultural knowledge to the lowest tactical level. Once the Soldier possesses enhanced cultural knowledge, this will improve his/her ability to recognize and document significant cultural information. Thus, the quality of observations by ES2 regarding cultural factors will improve.

This report will be made accessible through the World Wide Web (WWW) at URL:

<http://www.cecer.army.mil>

2 Toward a New Methodological Template for Spatial Decision Support System

The scientific study of insurgency and counterinsurgency, including the broad category of “deadly riots” (Horowitz 2001) is well established. Several historical conflicts have been examined in great detail by social scientists, military historians and policy analysts (e.g., Galuga 1964). Classic examples are the well documented analyses by the Rand Corporation of post World War II conflicts, such as the Vietnam war (Vietnam, Laos), but also insurgencies in other post-colonial conflicts such as Burma, Malaya, Rhodesia, the Philippines, El Salvador, and Colombia (for a recent overview, see Long 2006). Recently, interest has started to focus on the information requirements and capabilities specifically targeted at counterinsurgency (COIN), and the realization has gained ground that a specialized intelligence operations infrastructure must be developed, different from the support of traditional warfare (e.g., Gompert 2007, Libicki et al. 2007).

Specifically, in the context of the conflicts in Iraq and Afghanistan, there is a growing awareness that the traditional IPB needs to evolve significantly to meet the challenges presented in 4th generation warfare and a new infrastructure for information operations need to be developed. This infrastructure requires non-traditional information to be collected, relies heavily on human intelligence, the understanding of cultural and socio-economic factors and interpersonal networks, and increasingly employs spatially-explicit data and ethnographic intelligence (e.g., Hammes 2006, Renzi 2006, Zeytoonian 2006, Baker 2007).

This work approaches the development of actionable intelligence for counterinsurgency by drawing parallels with the study of civilian criminal events, such as homicides, vehicle thefts, and gang violence, and by exploiting the methodological approaches that emphasize spatially explicit information. This *spatial analysis of crime* (Anselin et al. 2000, Messner and Anselin 2004) builds on the well-established methods of spatial data analysis and spatial statistics, and applies these in the context of criminal events that occur at specific locations.

From a methodological perspective, the study of the location of violent events associated with an insurgency is a special case of “point pattern

analysis.” Interest focuses on the extent to which such events cluster in space and on the locations where those clusters (or “hot spots”) may be found. Increasingly, this also include attempts at explaining why the clusters are where they are as a function of covariates (explanatory variables) that can be readily measured. Point pattern analysis has seen extensive application in ecology, epidemiology as well as in crime analysis (a classic technical reference is Diggle 2003, a more introductory treatment and extensive references can be found in Waller and Gotway 2004). Such analyses of point events (or their aggregates by areal units) can be readily extended to applications in the context of military conflicts, such as improvised explosive device (IED) attacks (e.g., McFate 2005, Riese 2006, Suen and Demirci 2006).

The remainder of the report consists of five additional chapters. Chapter 3 (p 5) gives a general overview of the conceptual and methodological background in a brief discussion of spatial knowledge systems for crime analysis. This is followed by reviews of three methodological approaches that have seen extensive application in the spatial crime analysis literature: exploratory spatial data analysis (Chapter 4, p 9), explanatory modeling (Chapter 5, p 19), and surveillance/forecasting (Chapter 6, p 23). These topics are all addressed at a non-technical level; references are provided to the methodological literature for technical details and to specific applications in crime analysis for illustrations. Chapter 7 (p 25) concludes with a discussion of an initial framework for a methodological template to support actionable intelligence input into geospatial evidential reasoning.

3 Spatial Knowledge Systems for Crime Analysis

This chapter starts with a brief overview of the basic conceptual framework behind environmental criminology, i.e., the study of criminal events in which the “context” is viewed as providing important insight (e.g., as compared to a focus on the individual). Next, some important aspects of data integration are discussed, specifically with respect to the accuracy of spatially explicit information. Finally, some remarks are formulated on knowledge systems in support of crime analysis and how the various analytical techniques fit into these knowledge management systems.

Environmental criminology

The basic tenet in environmental criminology is that place influences crime. In other words, the location of criminal events is not random in space, and the structure of the patterns of these events can be linked to characteristics of the places where they occur, the places where the victims live and/or the locations of the perpetrators. In the criminology literature, two main theoretical frameworks have been developed to account for this. In one, termed “routine activities theory” or “crime pattern theory” (Cohen and Felson 1979, Brantingham and Brantingham 1981, 1984, Felson 1994), the crime generating/crime attracting activities of places are viewed as the central mechanism that brings both suitable targets and motivated offenders together in time and space. In the other, referred to as “social disorganization,” it is the local social and economic conditions of neighborhoods and the lack of local social control (collective efficacy) that creates conditions for elevated criminal behavior (e.g., based on the early findings of the “Chicago School” and more recently in the work of Sampson et al., such as Sampson et al. 1997, 2002).

Following the crime pattern theory, it is the daily routines of offenders in particular that are worthy of consideration. Accordingly, the places where offenders live, work, and play, and the pathways they follow to move around will help to explain geographic offending patterns. On the other hand, the social disorganization theory would stress that high crime neighborhoods are typically distinguished by poverty, residential instability, population heterogeneity, and family disruption. These neighborhoods have little social cohesion and are marred by physical disorder; they are

littered with trash, vacant and abandoned buildings, graffiti, and other signs of neglect. It is precisely in these types of neighborhoods that crime “hot spots” most often emerge.

These theoretical frameworks suggest that attention to space and place is warranted when trying to understand why violent events occur where they do. In the context of violent acts committed by insurgents, this suggests a number of potential aspects that should be taken into account. For example, routine activity would suggest that the places where people gather (e.g., markets) and the routes they follow (e.g., routes followed by military convoys) suggest more likely locations for attacks. Similarly, neighborhoods that have become socially dysfunctional and that lack cohesion would be potential “hot spots.” Paralleling efforts in the spatial analysis of crime, such a study of insurgent violence would move from the exploration to the explanation of patterns, leading to models that can be used as part of a knowledge system supporting policing and counterinsurgency.

A particularly relevant subset of crime analysis pertains to the study of gangs. In many respects, groups of insurgents share characteristics with gangs, and could be studied using conceptual and methodological frameworks that have been applied to gangs. Important aspects of these are the concept of micro locations, or “set space” where gangs tend to locate (Tita et al. 2005) and patterns of spatial diffusion of gang activity (Cohen and Tita 1999, Tita and Cohen 2004). A particularly promising approach is the combination of concepts from spatial interaction with concepts of network interaction (network or link analysis) in attempting to understand how the spatial imprint of gang activity matches their social interaction (Tita 2007, Tita and Ridgeway 2007). An illustration of the incorporation of insights from a spatial analysis into a gang intervention operation is given in Tita et al. (2003) for a case study in Los Angeles.

Data integration

Data from different sources need to be integrated into an operational decision support system. In the context of counterinsurgency operations, a distinction can be made between data on violent incidents (IED explosions, mortar attacks, riots) and data characterizing the “context” of these incidents (socio-demographic information on neighborhoods, physical characteristics, base maps, etc.).

Observations on incidents are typically geocoded as point locations (i.e., their coordinates or latitude-longitude are recorded), although the preci-

sion of the location may vary with the type of incident. For example, in some instances, only a vague reference to a particular location may be given, which precludes the use of point pattern analysis per se. Instead, analysis would have to be carried out at a spatially aggregated level. In contrast, observations on the cultural characteristics that may be used as explanatory variables for the patterns may be point locations (e.g., the location of physical facilities, such as bridges, religious buildings, police stations) or they may only be available at a spatially aggregate level, such as a neighborhood or a military grid (e.g., measures extracted from various text documents on commercial activity, number of jobs created, political activity, ethnic makeup). In addition, the spatial sampling of such data may be incomplete, requiring the application of spatial interpolation to obtain full coverage of the area of interest.

The effect of geocoding errors on the results of spatial analysis has received some attention in the literature, primarily in the context of protecting the privacy of medical records. In such instances, the original data are often perturbed (e.g., randomly moved about, or “jiggled”) or aggregated to a larger scale areal unit (e.g., sums of events by neighborhood, rather than individual addresses). A few studies have formally addressed how this affects the power of statistical tests and/or the quality of the coefficient estimates obtained. It is typically found that greater perturbation or aggregation lowers the power of tests. Examples are the study of the effect of aggregation on the power of cluster tests in Jacquez and Waller (2000), and on inference based on the much used scan statistic, as in Armstrong et al. (1999), Cassa et al. (2006), and Olson et al. (2006). The effect of masking on kriging interpolation and spatial autocorrelation analyses is addressed in Gabrosek and Cressie (2002) and Cressie and Kornak (2003). Again, not surprisingly, the quality of the statistical inference deteriorates with a decreased precision of the locations used as inputs. A recent study by Zimmerman and Pavlik (2008) confirms how multiple masked versions of the data and mask metadata affect the estimates of parameters in a clustered Poisson process. Further work in this area is needed to obtain general guidelines for use in operational settings.

A second important issue pertaining to data integration is the combination of observations at different spatial scales. This is referred to as the change of support problem (Gotway and Young 2002). A number of solutions have been proposed in the statistical literature, ranging from interpolating to a common aggregate frame to the combination of different spatial scales through hierarchical Bayesian modeling (e.g., Banerjee et al. 2004, Chap-

ter 6). An important methodological question is how sensitive the resulting inference is to decisions made about spatial scale and aggregation. A number of case studies address this in the context of spatial analysis of crimes and vehicle accidents (e.g., Thomas 1996, Wang 2005a). In addition, the cultural variables collected are likely to be of different quality and precision, some being only vague estimates or categories. This, in turn, will affect the precision of the end result.

Knowledge management systems

The ultimate objective of the spatial analysis of insurgent violence is a decision support system that can be used in day to day planning (actionable intelligence). The design of such systems has received considerable attention in crime analysis and several systems are currently in operational use by the police departments of larger metropolitan areas. A well known example is the so-called COPLINK system, which consists of software tools that extract information from various records and reports, combine data from different sources, discover patterns and implement link analysis and visualization in near real time (e.g., Chen et al. 2003, Chung et al. 2005, Xiang et al. 2005, Zhao et al. 2006).

Gottschalk (2006) outlines a conceptual framework and taxonomy of knowledge management systems in support of crime analysis. He outlines four stages with increasing sophistication, moving from general Information Technology (IT) support (such as spreadsheets), to information about knowledge sources (such as intranets), information representing knowledge (such as a data base, geodemographic profiles) and ending up with an expert system. The latter constitutes a complex knowledge system that take advantage of artificial intelligence to connect observed patterns to real time actions. Gottschalk (2006) coins the four stages as “officer-to-technology systems,” “officer-to-officer systems,” “officer-to-information systems,” and “officer-to-application systems.” A similar taxonomy can be used to aid in the design of knowledge management systems to support counterinsurgency, taking into account the special nature of information gained through various intelligence systems (human intelligences, sensors, etc.) and the different degrees of reliability of the data.

4 Exploratory Spatial Data Analysis of Crime

Arguably the first stage in a spatial analysis of crime is the exploratory stage. Exploratory data analysis (EDA) is a branch of statistics started by John Tukey (1977), and stresses an inductive approach. As spelled out by the statistician I.J. Good (1983), it is a collection of techniques used to discover potentially explicable patterns. The emphasis is on discovery of interesting patterns, which may be amenable to explanation, but the explanation itself is not part of EDA. EDA consists of many different graphical devices, such as charts, tables, graphs, and maps. These are referred to as views of the data, facilitating interactive discovery through a combination of graphical representations and summaries (Buja et al. 1996).

Exploratory Spatial Data Analysis (ESDA) is a superset of EDA that is focused on the spatial aspects of the data (Anselin 1999). This includes describing spatial distributions, identifying atypical spatial observations (spatial outliers, as distinct from regular outliers), discovering patterns of spatial association (spatial autocorrelation) and suggesting spatial regimes (spatial heterogeneity).

The techniques reviewed in this chapter are organized into four groups:

1. General crime mapping and geovisualization
2. Traditional point pattern analysis
3. Hot spot detection
4. Space-time exploration.

Crime mapping

In the late 1990s and early 21st century, the use of computerized crime mapping saw an explosive growth, reflected in several books and edited volumes devoted to the topic.

Early examples include Block et al. (1995), Eck and Weisburd (1995), Weisburd and McEwen (1997), LaVigne and Wartell (1998), and Harries (1999). Increasingly, the traditional mapping (choropleth maps) and basic spatial analysis operations (buffering, distance measures) are viewed as integral parts of a geographic information system and extended with more sophisticated (statistical) techniques to identify hot spots, highlight out-

liers, and suggest patterns, as argued in Anselin et al. (2000). Extensive illustrations can be found in Block (2000), Goldsmith et al. (2000), LaVigne and Wartell (2000), Hirschfield and Bowers (2001), Leipnik and Albert (2003), Boba (2005), Chainey and Ratcliffe (2005), Eck et al. (2005), Wang (2005b) and Ratcliffe (2006).

Basic geographic information system (GIS) use and computerized maps have become so standard in crime analysis that they will not be elaborated on here. Some specialized maps warrant a brief mention, however. For example, in Poulsen and Kennedy (2004), so-called “dasymetric maps” are used to depict the spatial distribution of burglaries in an urban area. These maps use additional GIS layers (such as housing units and land use) as a filter to constrain the area of administrative areal units to reflect more realistic locations for the crimes. In other words, these maps provide a compromise between assigning the same rate to the full administrative unit (the standard approach in choropleth mapping) and depicting the individual point locations. This is especially useful when the latter are not available and it avoids the potentially misleading effect of the area and arbitrary boundaries of administrative units typical of choropleth maps. Additional statistical maps can be used to avoid this problem, such as cartograms, animation and conditional maps (cf., Anselin et al. 2006). Also, specialized outlier maps can be employed to highlight locations with unusually high values (Anselin 1999, Anselin et al. 2004), or to identify sharp gradients in crime rates, i.e., so-called spatial outliers. For example, in Harries (2006) neighborhoods (census block groups) are identified where high quintile values are adjacent to low quintile values, suggesting an extreme crime gradient.

Additional methods, where the GIS and mapping are combined with pattern analysis, hot spot detection, and surveillance are treated in the next sections.

Pattern analysis

In this report, pattern analysis is used to designate traditional descriptive and exploratory methods of statistical spatial point analysis as well as data mining techniques that have evolved from the computer science literature. It is distinguished from hot spot detection (p 13), where the focus is on the use of indicators for spatial autocorrelation and clustering methods to identify regions of elevated crime incidence or risk.

Statistical analysis of point pattern

Descriptive statistics for point patterns include mean and median location and the standard deviational ellipse, which give an indication of the central tendency in the spatial distribution of the points and the spread and orientation of points around this center. These methods have been implemented in the widely adopted CrimeStat software package (Levine 2006, 2007) as well as in a number of other software tools and have been used in many applications. For example, LeBeau (1987) applied this technique to track the changes in the spatial pattern of rapes. These methods can also be readily incorporated into a GIS system in support of policing actions (e.g., to track the spatial dynamics of 911 calls).

A more refined technique to describe the spatial distribution of points is kernel smoothing, which creates a smooth surface representing the density of the points. In essence, this is a weighted moving average of the count of points within a circle of a given bandwidth, where the weights are given by the chosen kernel function (for detailed illustration, see, e.g., Levine 2007). Some examples of the application to spatial crime analysis are Steenberghen et al. (2004) who use it to describe the distribution of road accidents, and Corcoran et al. (2007) who include it into their review of spatial analytical methods applied to the study of fires.

Perhaps the most commonly used statistic to assess the absence of complete spatial randomness in a point pattern is Ripley's (1976) K function. The K function focuses on so-called second order properties of a point pattern, which are similar to the notion of a covariance. The first order characteristic is simply the intensity of the process, or the average number of points per unit area, for example, as summarized in a kernel density function. The second order characteristic is then some measure of covariance between intensities at different locations. More precisely, the K function is the ratio of the expected number of additional events within a given distance from an arbitrary event to the intensity of the process. It is readily calculated by counting the number of points within an increasing radius from each event in the pattern. It is typically computed for a number of distance ranges and plotted against distance. It is included as a function in the CrimeStat software and has seen many applications (see also Anselin et al. 2008).

While the K function focuses on the overall patterning of points ("clustering"), interest often centers on specific locations of "clusters." As such, the K function is not able to provide this information. An extension of the no-

tion of local indicators of spatial association (Anselin 1995) to identify local clusters by means of the differential of the K function, the so-called product density function, is advanced in Cressie and Collins (2001a, b). A slightly different approach was recently presented in Mateu et al. (2007).

One limitation of the K function as traditionally applied is that it is best suited for a situation of an isotropic plane, in which an event can be located anywhere. However, in practice, there are often limitations to the possible locations. For example, when events occur on a street network, the space in between the network links and nodes becomes impossible as a location. Recent work by Okabe and co-workers has extended the K function to events on a network, using shortest path distances on the network instead of the traditional omni-directional “as the crow flies” distance. The basic methodology was established in a series of papers by Okabe et al. (1995), Okabe and Kitamura (1996), Okabe and Yamada (2001), and Okabe and Satoh (2005), and it has been implemented in the SANet toolbox for spatial analysis on a network (Okabe et al. 2006a, b).

The network K function has seen applications in a number of areas, such as the location of acacia plants (Spooner et al. 2004) and accidents on a road network (Yamada and Thill 2004; e.g., contrast with a traditional K function analysis of traffic accidents in Jones et al. 1996). Yamada and Thill (2004) also carry out a comparison of the results of the traditional (planar) K analysis with the network K function. Similarly, in Lu and Chen (2007), the results of a planar and network K are compared for urban crime on a street network. The planar K tends to result in false positives for a less dense street network and low crime density; in contrast, dense street and dense crime lead to more false negatives. In other words, the performance of the network K function relative to the planar K is related to the structure of the street network and the density of point events. Further work is needed to establish the degree of generality of the findings in this case study.

Data mining

Parallel to the attention paid to pattern recognition from a statistical viewpoint, developments in computer science have yielded methods of machine learning and knowledge discovery that are designed to recognize patterns in multivariate data sets. In crime analysis, this begins with automatic information extraction from various records and incident reports and the application of machine learning (such as text mining) and rule-based expert systems to ultimately yield an operational decision sup-

port system. A recent overview of the application of data and text mining in crime analysis, with an emphasis on risk and threat assessment, and the use of predictive analytics to obtain operationally actionable output is given by McCue (2007). Discussions of different approaches can also be found in Brown and Hagen (2003), Chen et al. (2003), and Yang and Li (2007). Arguably the best-known system in operational use to date is the COPLINK system referred to in Section B.3.

Hot spot detection

Specialized techniques for the detection of hot spots follow a number of different logics. Three different categories are distinguished here: scan statistics, methods based on spatial autocorrelation statistics, and generic cluster detection techniques. They are briefly reviewed in turn.

Scan statistics

So-called scan statistics consist of counting the number of events in a geometric shape (usually a circle) and comparing those to a reference pattern of spatial randomness. Early examples are the Geographical Analysis Machine (GAM) of Openshaw et al. (1987), and the space-time analysis of crime (STAC) of Block (1995, 2000). Both of these methods consist of counting the number of points in a series of overlapping circles and labeling them as significant when the observed count is extreme relative to a reference distribution of simulated spatially random points. The STAC method is implemented in the CrimeStat software package, in which an identified cluster of points is represented by their standard deviational ellipse (see centrography in c.2.1).

These early scan statistics suffer from the problem of multiple comparisons (overlapping circles) and are sensitive to parameter settings (radius of circle, etc.). The Kulldorff (1997, 1999) scan statistic and its later refinements address some of these concerns by using a likelihood criterion to identify clusters. In essence, the scan statistic considers circles of increasing radius and identifies that circle that maximizes the probability of having events inside the circle exceeding that outside the circle. Kulldorff's scan statistic is implemented in the specialized SatScan software package (<http://www.satscan.org>). A recent generalization to the detection of arbitrarily shaped hotspots is the so-called upper level set (ULS) scan statistic (Patil and Taillie 2003) and its extension to bivariate data contexts in Modarres and Patil (2007).

An alternative extension is the augmentation of the likelihood idea of the scan statistic with an optimization procedure using simulated annealing to detect spatial clusters of arbitrary shape by Duczmal and Assuncao (2004). This is applied to the identification of clusters in the spatial distribution of homicides in Belo Horizonte, Brazil.

Spatial autocorrelation statistics

A second broad category of approaches bases the identification of clusters and spatial outliers on the results of a statistical test for spatial autocorrelation. These methods pertain to data that have been aggregated into areal units, such as administrative units or artificial grids, so called lattice data (contrasting with point patterns). For example, in spatial crime analysis, this often pertains to the count of events by spatial unit, or to a rate (the count of events divided by the population at risk).

A spatial autocorrelation statistic is a formal test of the match between value or attribute similarity and locational similarity. The statistic summarizes both aspects and is deemed to be significant if the probability (p-value) that the statistic would take this value in a spatially random pattern is extremely low. Measures of attribute similarity summarize the similarity (or dissimilarity) between the values observed at two locations. Three popular formal expressions for this are the cross product (as a measure of similarity), and the squared difference and absolute difference (as measures of dissimilarity). Locational similarity is formalized through a spatial weights matrix, which expresses the notion of neighbor. Spatial weights are not necessarily geographical, but can incorporate social network structures as well (for a classic treatment of spatial autocorrelation, see Cliff and Ord 1973, 1981).

Similar to the K function for point pattern analysis (p 11), a global spatial autocorrelation statistic (like Moran's I or Geary's c) is not appropriate for the identification of local clusters or hot spots. To that end, a local version of the statistics needs to be employed, a so-called "Local Indicator of Spatial Association," or LISA (Anselin 1995). Significant LISA statistics suggest locations where the value of the variable of interest is more grouped with that of its neighbors than likely under spatial randomness. Therefore, such locations become identified as local clusters, either hot spots (high values surrounded by other high values), or cold spots (low values surrounded by low values). Alternatively, in some instances spatial outliers may be identified by significant LISA statistics indicating negative local

spatial autocorrelation, where low values are surrounded by high values, or vice versa.

A commonly used LISA statistic is the local Moran, a location-specific version of the familiar Moran's I statistic for spatial autocorrelation (Anselin 1995). This has been applied to the identification of high homicide county clusters in Messner et al. (1999), for example (for more extensive overviews, see also Messner and Anselin 2004 and Anselin et al. 2008). A related application is to the identification of so-called black zones, or road segments that exhibit an extreme number of vehicle accidents (for an early approach, see Black and Thomas 1998). Local Moran statistics are used to identify significant concentrations of high accident numbers in Flahaut et al. (2003) and Steenberghen et al. (2004) (see also Geurts et al. 2004, for an assessment of methods to identify and rank black zones). A related approach is the extension of the network K function and the LISA statistic to local indicators of network constrained clusters (LINCS) in Yamada and Thill (2007). This is also used to identify segments on a road network with elevated numbers of vehicle crashes.

A slightly different local statistic is the Gi (and Gi*) test developed by Getis and Ord (1992) (see also Ord and Getis 1995). Similar to the local Moran, this statistic identifies locations of local hot spots and local cold spots (but not spatial outliers). It has been applied to the study of burglaries in urban areas by Craglia et al. (2000). Interestingly, in that study, the Gi statistic is compared to the more traditional STAC approach and found to be superior in identifying true clusters. Ratcliffe and McCullah (1999) use the Gi statistic in combination with a global moving window to distinguish between hotspots and hotbeds in residential burglary and motor vehicle crime. They suggest that some of the problems caused by the modifiable areal unit problem (MAUP) are avoided by changing the search area of the moving window.

Local spatial autocorrelation measures are included in the software GeoDa (Anselin et al. 2006), Space-Time Analysis of Regional Systems (STARS) (Rey and Janikas 2006), CrimeStat (Levine 2006), the ArcGIS spatial statistics toolbox, the open source R spdep (spatial dependence) package, as well as several others.

Generic cluster detection

A third category of methods to detect hot spots uses heuristic methods from the discipline of operations research to construct clusters of areas

that are similar with respect to some characteristic. These techniques can be applied to individual points or to aggregate spatial units. Specifically, clusters are formed such that the similarity of the cluster members within the same cluster is greater than between clusters. Similarity can be based on distance or on a multivariate characterization (as in k-means clustering). Applications of these techniques to urban crime in Queensland are illustrated in Murray et al. (2001) (see also Murray and Estivill-Castro 1998).

A recent article by Grubestic (2006) suggests that fuzzy clustering techniques may be superior in some respects relative to the standard hierarchical clustering techniques. Such fuzzy methods do not yield “hard” membership in each partition, but instead yield a degree of fuzziness. This creates some challenges for the visualization of the results, e.g., by means of membership probability surfaces. Grubestic (2006) illustrates this with an application to crime events in a neighborhood in Cincinnati, Ohio. Related approaches are so-called contiguity-constrained clustering methods (Duque et al. 2007a, b), where it is guaranteed that the identified clusters consist of connected spatial units, which is not always the case when using standard clustering algorithms, such as the k-means clustering contained in CrimeStat.

Space-time exploration

Many techniques to explore patterns that occur both across space and over time are straightforward generalizations of pure cross-sectional methods. For example, the scan statistic (C.3.1) can be extended to identify space-time clusters, the local Moran statistic (C.3.2) can be applied to compare patterns of occurrence with that of neighbors at a different point in time, etc. The research question at hand is very similar to that employed in epidemiological studies of the spread of disease. In spatial crime analysis, the counterpart of this is the notion that the risk of a particular criminal event spreads over time to nearby locations. Space-time exploration has many commonalities with the surveillance and forecasting methods discussed in Section E. The distinction between the two categories is admittedly somewhat arbitrary. In Section E, the emphasis is on methods that have been expressly presented in a context of surveillance and forecasting, whereas the methods covered here are more in an exploratory vein, without necessarily being used in an explicit surveillance context.

A commonly used procedure inspired by the statistical point pattern literature is the Knox test to identify space-time clusters (see Diggle 2003). For

example, this was applied in a wide ranging comparison of space-time patterns in burglaries across 10 urban areas (Johnson et al. 2007). A similar extension is the random point nearest neighbor technique of Ratcliffe (2005), which is applied to the change in the spatial distribution of burglaries in Canberra, Australia.

A related interest in the study of the “contagion” of crime risk is whether some type of displacement may occur, particularly due to a previous police intervention. This focus on displacement is the topic of a number of efforts, such as the so-called aoristic signatures of Ratcliffe (2000, 2002) and the weighted displacement quotient of Bowers and Johnson (2003). Aoristic signatures are a method to deal with the imprecision in the recorded time of the criminal event. A temporal weight is constructed to reflect the probability that an event occurred in a given period. These weights can be attached to the spatial locations of the events and yield different visualizations (e.g., the cylinders used in Ratcliffe 2000) and surface representations. The weighted displacement quotients uses a similar rationale as local space-time autocorrelation quotients in that changes in the crime rate in a buffer zone are examined around the original location of criminal events. This yields some sort of location quotient that incorporates a measure of change over time (see Bowers and Johnson 2003).

Other approaches consist of creative extensions of cartographic techniques to capture the spatial dynamics of criminal events. As reviewed in Brundson et al. (2007) exploratory space-time visualization can be carried out by means of map animation, creative use of so-called comaps, isosurfaces, and linked plots.

Griffith and Chavez (2004) use an innovative combination of local spatial autocorrelation statistics (i.e., ESDA) with the trajectory method proposed by Nagin (1999) to study the space-time dynamics of crime in Chicago neighborhoods. Applying the trajectory method to the crime patterns over time for each neighborhood studied yields a grouping of neighborhoods by trajectory type. This is then examined by means of local spatial autocorrelation statistics to assess the extent to which neighborhoods with similar trajectories also cluster in space.

A similarly creative combination of techniques is the use of circular statistics to compare the dynamics of criminal events outlined in Brundson and Corcoran (2006). The circular statistics (originally developed to analyze directional patterns) are adapted to assess and model geographical pat-

terns in the daily cycles of events. Specifically, Brunsdon and Corcoran (2006) apply this to study criminal damage in the city of Cardiff, Wales and use a kernel smoothing technique to visually represent the distribution by time of day. This is then applied to a geographical comparison between the city center and the rest of the city.

5 Explanatory Modeling of Crime

Explanatory modeling of crime moves beyond exploration and identification of patterns to the modeling of crime event counts, rates, or risk as a function of explanatory variables, or covariates. The covariates are typically suggested by theoretical frameworks in environmental criminology (B.1) and include characteristics of the perpetrator, victim, the location where the event(s) happened, and the environmental context. In this section, these approaches are classified into three broad categories:

1. Traditional regression modeling, where the crime event is on the left hand side of an equation and the covariates are on the right hand side
2. A special case of regression modeling, where the focus is on repeat offenders and the use of geographic characteristics (such as distance to the event) to model the probability of an additional event occurring in a particular location
3. A brief review of simulation approaches in the form of agent-based models.

Regression models

The environmental tradition in criminology has yielded a vast number of regression analyses where the rate of one or more types of violent crime (homicides, burglaries, etc.) in a spatial unit of reference is related to a set of covariates (for overviews, see Anselin et al. 2000; Messner and Anselin 2004). Such ecological regression has been carried out for a range of different spatial scales, such as neighborhoods, census tracts, counties and metropolitan areas, both in a pure cross-section as well as including observations over time and across space.

Covariates commonly consist of neighborhood characteristics (based on the social disorganization tradition), such as socio-economic conditions, deprivation, residential stability, ethnicity, education, as well as characteristics of locations that would be conducive to crime (routine activities), such as presence of (or distance to) liquor stores and bars. Typically, these covariates are extracted from census sources, sometimes reduced in dimension by means of factor analysis (due to the high degree of collinearity).

Apart from various empirical applications (too numerous to be reviewed here), attention also focuses on some important methodological concerns, particularly dealing with the spatial nature of the data (spatial econometrics) and assessing different estimation methods.

The use of cross-sectional data for aggregate spatial units requires an explicit consideration of spatial consideration and spatial heterogeneity, which is accomplished by means of the methodology of spatial econometrics (Anselin 1988). In Baller et al. (2001), the importance of using the proper spatial econometric estimation methods is illustrated for a study of homicide rates in U.S. counties. They use a classical perspective and limit the discussion to linear regression models and the application of spatial lag and spatial error models. A Bayesian perspective is taken in the work of Law and Haining (2004), where spatial autocorrelation is taken into account in a logistic regression through a random effects specification in a Bayesian hierarchical model of high intensity crime areas in Sheffield, England. This extends earlier studies that used standard logistical regression techniques (Craglia et al. 2004, 2005). Malczewski and Poetz (2005) address spatial heterogeneity explicitly by applying the geographically weighted regression method (GWR, Fotheringham et al. 2002) in a study of residential burglaries in London, Ontario. Wang (2005a) focuses on the role of spatial scale and the associated MAUP by considering spatial aggregation at different scales.

Most studies consider crime data as continuous variables, aggregated to spatial units. In contrast, Osgood (2000) takes into account the discrete count nature of criminal events through the application of Poisson regression. Another important category consists of studies where criminal behavior is conceptualized as a choice process. For example, in Xue and Brown (2003, 2006) crime is analyzed within the methodological framework of discrete choice theory. In addition, some innovative techniques are introduced to proxy unobserved actual choice behavior by characteristics of the environment, such as distance to various “features.” In Haynie et al. (2006) neighborhood characteristics and peer influence (social networks) are considered explicitly in a study of adolescent violence.

Panel data, i.e., combinations of observations across space and over time, have been considered as well, particularly in an attempt to eliminate unobserved heterogeneity. Most of these use the standard fixed effects or random effects methods. Particular attention to methodological issues is given by Worrall and Pratt (2004), where the focus is on dealing with unob-

served heterogeneity and Kakamu et al. (2008), where Bayesian spatio-temporal models are applied. Phillips and Greenberg (2008) compare several methods for pooled cross section and time series data, such as fixed effects and random effects, as well as an innovative use of latent growth curve models.

An interesting specialized literature deals with explanatory regression models for road accidents, i.e., models that provide explanation for the location of black zones (road segments with elevated accident counts). For example, Flahaut (2004) uses a logistic regression with spatial autocorrelation to this effect. Somewhat related is the analysis of motor vehicle accident injuries in McNab (2004), where a Bayesian random component model is used to account for spatial autocorrelation.

Geographic profiling

A special case of explanatory models is so-called geographic profiling, where the objective is to derive the residence of a serial offender from the locations of the successive crimes (Canter 2003, Rossmo 2005). The argument is that offenders are most likely to strike within their own activity space, so that a geographic strategy based on the spatial distribution of the events or on the distance from various candidate locations to the crime events provides important insights. Geographic profiling has seen a range of application, such as tracking serial killers (Canter et al. 2000) or commercial robberies (Laukkanen and Santilla 2006). Several methodological aspects have received attention, such as the effectiveness of decision rules of differing complexity (Snook et al. 2005) and the sensitivity of the distance decay function to the choice of distance measure, such as shortest distance or travel time (Kent et al. 2006). The distance decay function that underlies geographic profiling is part of several software packages developed to assist police investigators. This includes Dragnet (Center for Investigative Psychology, University of Liverpool*), CrimeStat (Levine 2007†), psycho geographic profiling Predator (Godwin and Rosen 2005), and Rigel (Environmental Criminology Research Inc.‡).

The latter uses a patented Geographic Criminal Targeting (GCT) algorithm. Similar in spirit to geographic profiling are threat maps based on an index of vulnerability that is built up from accessibility measures to a

* <http://www.ipsy.com/publications/publications dragnet.php>

† <http://www.icpsr.umich.edu/CRIMESTAT/>

‡ <http://www.ecricanada.com/rigel/index.html>

number of features in the landscape (e.g., Suen and Demirci 2006; Riese 2006). Again, the fundamental driver is a distance decay function, reflected through a particular accessibility index or a spatial kernel function.

Agent-based models

An alternative approach towards gaining an understanding of criminal behavior is not based on the analysis of actual data, but on the simulation of complex systems, driven by the behavior of individual agents. So-called agent-based modeling is increasingly applied in the modeling of military conflicts such as urban insurgency (Diedrich et al. 2003). The use of a multi-agent approach has also gained acceptance in criminology as a way to obtain insight into the complex interactions involved in criminal behavior, such as street robbery or riots (e.g., Groff 2007, Torrens 2007a, b). However, to date, the computational and data requirements needed to mimic realistic contexts still require considerable further research.

6 Surveillance and Forecasting

Several of the techniques reviewed under the heading of space-time exploration (c.4) and regression analysis (D.1) have been and could be implemented as part of surveillance systems aimed at detecting important changes in patterns over time. Such systems have a strong tradition in epidemiology and public health analysis, where they are used to detect the advent of a new epidemic or to identify an unusual outbreak of a disease. The ultimate goal of surveillance methods is to develop an automated decision support system that provides “alerts” when needed.

A number of point pattern techniques have been suggested specifically in the context of surveillance. For example, the spatial scan statistic of Kulldorff (2001) can be readily implemented to accomplish this. Also, Rogerson (2001) and Rogerson and Sun (2001) track the change over time in the spatial pattern of point events by combining a nearest neighbor statistic and a cumulative sum method. Porter and Brown (2007) suggest a method to detect the change in the distribution of point process by constructing an intensity function that depends on features (such as distance to landmarks) as a special case of marked point pattern analysis.

An alternative perspective is based on the time domain and uses forecasting methods. This is more appropriate in allocating future crime fighting resources, for example, future deployment of police forces. In the context of a spatial analysis of crime, forecasting is relevant when a locational component is preserved. To have sufficient statistical validity, the spatial units of analysis will typically be fairly aggregate. In many instances, this precludes a meaningful spatial analysis.

A special issue of the *Journal of Forecasting* (Gorr and Harries 2003) considers a number of methodological issues pertaining to crime forecasting, such as the accuracy for small areas (Gorr et al. 2003). A number of novel combinations of techniques are suggested as well, such as the use of “features” to model the transition density between patterns of events over time in Liu and Brown (2003), and the combination of cluster detection with an artificial neural network forecasting routine in Corcoran et al. (2003).

One common characteristic of crime forecasting techniques is the need for considerable data points, both over time and across space. This is not likely to be satisfied in a counterinsurgency context.

7 Towards a Methodological Template

From a methodological viewpoint, the parallel between the development of actionable intelligence for counterinsurgency and the techniques developed for the spatial analysis of crime is attractive. However, several limitations need to be considered before any of these methods can be applied directly to a situation of urban military conflict. The main constraint pertains to the quality and availability of the data. Most methods of spatial data analysis are based on an assumption of either a complete count of events (e.g., in point pattern analysis) or a well-structured sample (e.g., the basis for census data). Neither of these can be expected to necessarily hold in a violent conflict situation. As pointed out in the report, in addition there may be lack of information about the exact location of events as well as imprecision in the measurement of neighborhood and other socio-cultural characteristics.

Therefore, a high priority of research is to assess the extent to which the conclusions drawn from the application of exploratory and explanatory spatial data analysis remain reliable under conditions of imprecise information. This may lend itself to the application of a Bayesian perspective, where the uncertainty about both data and parameters can be formally expressed. Alternatively, simulation experiments may provide insight into the information loss incurred as a result of imperfect measurement and sampling. To date, the ramifications of this in the context of the types of analyses required here have not been explored.

A methodological template would then consist of a three-pronged strategy, going from exploration of patterns (pattern analysis, data mining) to the formulation of an explanatory model (relating events, rates or risk to socio-cultural covariates) and the incorporation of these into a decision support system. A major focus of attention would be to identify those types of events and those socio-cultural characteristics that can be extracted from non-traditional data sources (e.g., text mining of news reports). In a first stage of analysis, these variables can be turned into indicators, categories or indexes that could be mapped, and whose pattern structure could be followed over time. In a second stage of analysis, those variables could be included as covariates in an explanatory model to provide the basis for surveillance and/or forecasting analysis.

Acronyms and Abbreviations

Term	Spellout
ACUSTO	Actionable Cultural Understanding for Support to Tactical Operations
ANSI	American National Standards Institute
ASAALT	Assistant Secretary of the Army for Acquisition, Logistics, and Technology
CERL	Construction Engineering Research Laboratory
COIN	Counterinsurgency
DC	District Of Columbia
EDA	Exploratory Data Analysis
ERDC	Engineer Research and Development Center
ESDA	Exploratory Spatial Data Analysis
GAM	Geographical Analysis Machine
GCT	Geographic Criminal Targeting
GIS	Geographic Information System
GWR	Geographically Weighted Regression
IAT	Intelligent Agent Technology
IED	Improvised Explosive Device
IEEE	Institute of Electrical and Electronics Engineers
IPB	Intelligence Preparation of the Battlefield
IT	Information Technology
LINCS	Local Indicators of Network Constrained Clusters
LISA	Local Indicator of Spatial Association
MAUP	Modifiable Areal Unit Problem
MDMP	Military Decision Making Process
NSN	National Supply Number
OMB	Office of Management and Budget
SANet	[Toolbox for] Spatial Analysis on a Network
STAC	Spatial and Temporal Analysis of Crime Package
STARS	Space-Time Analysis of Regional Systems
TR	Technical Report
UK	United Kingdom
ULS	Upper Level Set
VISTA	Visualization Of Threat And Attacks

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14. ABSTRACT This report approaches the development of actionable intelligence for counterinsurgency by drawing parallels with the study of criminal events such as homicides, vehicle thefts, and gang violence, and by exploiting the methodological approaches that emphasize spatially explicit information. This spatial analysis of crime builds on the well-established methods of spatial data analysis and spatial statistics, and applies these in the context of criminal events that happen at specific locations. The theoretical background for these methods is drawn from environmental criminology. Methods are categorized into three main groups: exploratory spatial data analysis, explanatory spatial modeling, and surveillance/forecasting techniques. The basic principles are outlined and examples provided that illustrate the application specific techniques in crime analysis. An initial methodological template is formulated that stresses the constraints imposed by the quality and quantity of spatially specific information available in a counterinsurgency context.					
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